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Segmentation of Diffusion Tensor Brain Tumor Images using Fuzzy C-Means Clustering

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Abstract: **A malignant tumor, also called brain cancer, grows rapidly and often invades or crowds healthy areas of the brain. Brain tumors can affect white matter fibers by either infiltrating or displacing the tissue. When the myelin sheath is damaged or disappears, the conduction of impulses along nerve fibers slows down or fails completely. Diffusion Tensor Imaging (DTI) is a relatively new imaging technique that can be used to evaluate white matter in the brain. DTI has diagnostic implications by being able to pinpoint areas where normal water flow is disrupted, providing valuable information about the location of specific lesions. Edema, infiltration and destruction of white matter reduces the anisotropic nature of the white matter. The paper aims to segment tumor from the healthy brain tissues in Diffusion Tensor brain tumor images using Fuzzy C-Means clustering**

Tumor; diffusion tensor image; edema; anisotropy; clustering (key words)

I. INTRODUCTION

A brain tumor is a group of abnormal cells that grows in or around the brain. Tumors can directly destroy healthy brain cells. According to WHO, there are an estimated 240,000 cases of brain and nervous system tumors per year, worldwide.

Brain tumors are either malignant or benign. A malignant tumor, also called brain cancer, grows rapidly and often invades or crowds healthy areas of the brain. Benign brain tumors do not contain cancer cells and are usually slow growing. Brain tumors fall into two different categories: primary or metastatic. Primary brain tumors begin within the brain. A metastatic tumor is formed when cancer cells located elsewhere in the body break away and travel to the brain.

The brain of human consists of gray matter and white matter. The gray matter contains the nerve cells. The white matter of the brain is composed of nerve fibers and myelin. The nerve fibers form the connections between the nerve cells. Myelin is an essential part of the white matter. Brain tumors can affect white matter fibers by either infiltrating or displacing the tissue. When the myelin sheath is damaged or disappears, the conduction of impulses along nerve fibers slows down or fails completely. Consequently, brain functions become hampered or be lost.

Neuroimaging techniques are used to produce images of the brain. Each technique conveys distinct types of information depending on the question at hand. MRI is the primary imaging modality in brain tumor patients. Diffusion Tensor Imaging (DTI) is a relatively new imaging technique that can be used to evaluate white matter in the brain. DTI has diagnostic implications by being able to pinpoint areas where normal water flow is disrupted, providing valuable information about the location of specific lesions.

Brain tumors alter regional brain architecture due to differences in cell structure, size, and density and the presence of necrosis and edema. Consequently, tumor MR diffusion properties may identify diagnostic intertumoral differences. Whole-brain maps of diffusion metrics can be generated from diffusion tensor imaging (DTI) data. Mean diffusivity (MD) provides a magnitude of isotropic diffusion (in $mm^2 s^{-1}$), and fractional anisotropy (FA) provides a scalar value of diffusion directionality. Differences in MD and FA among tumor types and grades of malignancy have been investigated with mixed success.

The diffusion of water within the tissues will be altered by changes in the tissue microstructure and organization. Edema, infiltration and destruction of white matter reduces the anisotropic nature of the white matter. DTI can delineate gross abnormality in the white matter anatomy better than conventional MRI. DTI can also be used to differentiate tumor-infiltrated edema from pure vasogenic edema, which may be beneficial for accurate preoperative diagnosis of glioblastomas and metastasis. DTI can be used to differentiate between recurrent tumor and radiation necrosis as in [11]

II. RELATED STUDIES

Diffusion tensor imaging (DTI) has become one of the most popular MRI techniques in brain research, as well as in clinical practice.

A significant number of studies have attempted to use DTI to more precisely delineate the margins of brain

tumors in humans and detect changes in the normal-appearing tissue surrounding malignant gliomas that are not detectable on conventional MR imaging. DTI has been utilized for evaluating the peritumoral region of brain tumors is discussed in [1].

Conventional structural MR modalities are combined with diffusion tensor imaging data to create an integrated multimodality profile for brain tumors. This framework is discussed in [2]. DTI-based histogram and fDM analysed for evaluating the early effects of temozolomide (TMZ) chemotherapy in low-grade glioma patients have been explored in [3].

Reference[4] presents a novel whole-brain diffusion tensor imaging (DTI) segmentation to delineate tumor volumes of interest (VOIs) for subsequent classification of tumor type. It uses isotropic and anisotropic components of the diffusion tensor to segment regions with similar diffusion characteristics.

In the findings of the paper[5], DTI is the only approach available to track brain white matter fibers noninvasively .

III. RATIONALE OF THE STUDY

For effective brain tumor treatment, an accurate identification of boundaries between tumor, edema and healthy tissue is critical in brain tumor patients. This is very challenging mainly owing to the fact that high-grade tumors are inherently diffuse and infiltrative and invade the surrounding healthy tissue.

Tumors are heterogeneous, comprising enhancing and non-enhancing tumor tissue types and edema, rendering the transition from tumor to healthy tissue gradual. It is therefore challenging, if possible at all, to identify a clear transition from healthy tissue to edema to tumor by an inspection of the conventional MR images.

Differentiation of tumor recurrence from treatment-related changes may be difficult with conventional MR imaging when newly enhancing lesions appear. This leaves recurrent brain tumor tissues untreated, likely leading to faster tumor spread and lowers the chance of survival. The study aims to differentiate tumor from the healthy brain tissues and the edema using Diffusion Tensor brain Images in brain tumor patients.

IV. PROPOSED WORK

The sequence of operations for identification of boundaries between tumor, edema and healthy tissue in diffusion tensor MRI images of brain contain various steps like image preprocessing and enhancement, image segmentation,feature extraction and classification.

a. Image preprocessing and enhancement

Before detecting the tumor in the image, preprocessing is done for increasing the reliability of optical inspection. Initially the DTI mages of brain are acquired and they are pre-processed in order to extract the necessary information. During the process of image formation, the quality of images may degrade due to variety of causes such as out of focus, presence of noise, distortion of optical systems, the relative motion between the camera and the scene etc. Image is converted from RGB to grayscale mode. The grayscale is then enhanced to increase the quality of the image by applying median filter. Plot the histogram to study the strength of the pixels.

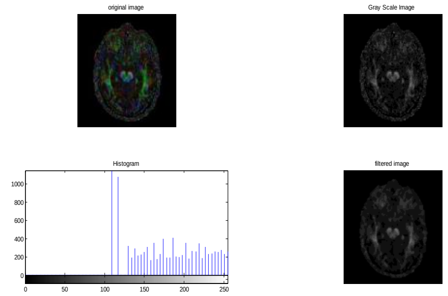

Fig 1: Image after preprocessing

b.Image Segmentation

Segmentation is the process of dividing an image into regions with similar properties such as gray level, color, texture, brightness, and contrast. The main goal in brain diffusion tensor MRI segmentation is to segment gray matter, white matter and cerebrospinal fluid. Segmentation is also used to find out the regions corresponding to tumors, edema, and other pathologies. The aim of medical image segmentation is to study anatomical structure, identify Region of Interest(ROI) i.e. locate tumor, measure tissue volume to measure growth of tumor and helps in treatment planning prior to radiation therapy.

Automatic segmentation of medical images is a difficult task as medical images are complex in nature and rarely have any simple linear feature. Although a number of algorithms have been proposed in the field of medical image segmentation, medical image segmentation continues to be a complex and challenging problem.

1. *Artificial Intelligence Tools for Segmentation and Classification*

Automatic segmentation methods have been based on artificial intelligence (AI) based techniques. AI techniques can be classified as supervised and unsupervised. Supervised segmentation requires operator interaction throughout the segmentation process whereas unsupervised methods generally require operator involvement only after segmentation is complete. Unsupervised methods are preferred to ensure a reproducible result; however, operator interaction is still

required for error correction in the event of an inadequate result.

1.1 Supervised method

In the supervised category, Artificial Neural Network (ANN) based algorithms are mostly used. ANN is composed of large number of interconnected processing elements (artificial neurons) working in unison to solve specific problems.

The main advantages of ANN are:

- ability to learn adaptively, using training data to solve complex problems.
- it can create its own organization depending upon the information it receives during learning time
- capability of performance in real time because of parallel configuration

1.2 Unsupervised Method

Most of the unsupervised algorithms are cluster based and not dependent on training and training data. The two commonly used algorithms for clustering are K-mean or Hard C-mean and Fuzzy C-means. K-means algorithm produces results that correspond to hard segmentation while fuzzy C-mean produces soft segmentation which can be converted into hard segmentation by allowing the pixels to have membership of cluster in which they have maximum value of membership coefficients.

1.2.1 Fuzzy c-Means algorithm

Clustering is the process of finding natural grouping clusters in multidimensional feature space. It is difficult because clusters of different shapes and sizes can occur in multidimensional feature space. A number of functional definitions of clusters have been proposed. Patterns within a cluster are more similar to each other than patterns belonging to different clusters. Image segmentation may be considered a clustering process in which the pixels are classified into the attribute regions based on the texture feature vector calculated around the pixel local neighbourhood. The Fuzzy c-Means algorithm is a clustering algorithm where each item may belong to more than one group (hence the word *fuzzy*), where the degree of membership for each item is given by a probability distribution over the clusters.

Since the absolute membership is not calculated, FCM can be extremely fast because the number of iterations required to achieve a specific clustering exercise corresponds to the required accuracy.In each iteration of the FCM algorithm, the following objective function JJ is minimised:

$$J=\sum_{i=1}^{N} \sum_{j=1}^{C} \delta_{ij} \|x_i - c_j\|^2$$

Here, N is the number of data points, C is the number of clusters required, c_j is the centre vector for cluster jj, and δ_{ij} is the degree of membership for the ith data point x_i in cluster j. The norm, $\|x_i - c_j\|$ measures the similarity (or closeness) of the data point x_i to the centre vector c_j of cluster j. In each iteration, the algorithm maintains a centre vector for each of the clusters. These data-points are calculated as the weighted average of the data-points, where the weights are given by the degrees of membership.

For a given data point xi, the degree of its membership to cluster j is calculated as follows:

$$\delta ij = \frac{1}{\sum_{i=1}^{C} (\|x_i - c_j\| \| x_i - c_k\|)^{2/m-1}}$$

where, m is the fuzziness coefficient and the centre vector c_j is calculated as follows:

$$c_j = \frac{\sum_{i=1}^{N} \delta^{m}_{ij}.x_i}{\sum_{i=1}^{N} \delta^{m}_{ij}}$$

where δ_{ij} is the value of the degree of membership calculated in the previous iteration. Note that at the start of the algorithm, the degree of membership for data point i to cluster j is initialised with a random value θ_{ij}, $0 \leq \theta_{ij} \leq 1$.

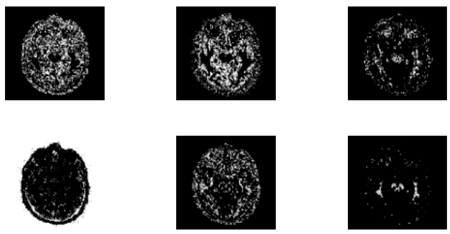

Fig 2: Fuzzy C-Means clustered image(6 clusters)

V. CONCLUSION

In this paper an algorithm using Matlab has been devised for the segmentation of brain tumor from DTI brain scanned images based on a range of operations like pre-

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processing, Fuzzy C-means. The effectiveness of FCM is comparatively better than K means algorithm for overlapped datasets. In future, this system can be implemented with some other algorithm which will give more accuracy and save more time.

REFERENCES

[1] Sternberg EL, et al., " Utility of Diffusion Tensor Imaging in Evaluation of the Peritumoral Region in Patients with Primary and Metastatic Brain Tumors", Americal Journal for Neuroradiology, 2014, Volume 35, Issue 3, pp:439 -444

[2] Hongmin Cai, et al.,"Probabilistic Segmentation Of Brain Tumors Based On Multi-Modality Magnetic Resonance Images" in Proceedings of the IEEE International Symposium on Biomedical Imaging: from Nano to Macro, 2007.

[3] Antonella Castellano, et al.,"Evaluation of low-grade glioma structural changes after chemotherapy using DTI-based histogram analysis and functional diffusion maps" European Radiology, 2016, Volume 26, Issue 5, pp: 1263-1273.

[4] Timothy L. Jones, Tiernan J. Byrnes, et al., "Brain tumor classification using the diffusion tensor image segmentation (D-SEG) technique" Neuro-oncology, 2015, Volume 17, Issue 3, pp: 466-476.

[5] Denis Le Bihan, Jean-Francois Mangin, "Diffusion Tensor Imaging : Concepts and Applications" Journal of Magnetic Resonance Imaging, 2001, Volume 13, pp:534-546

[6] Mori Susumu and J Donald Tournier, Introduction to diffusion tensor imaging and higher order models (Second edition) Academic Press, Oxford, UK, 2014.

[7] B. H. Menze, M. Reyes, K. Van Leemput, et al., " The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)" *IEEE Transactional Medical Imaging, 2015*, Volume 34, Issue 10, pp: 1993-2024.

[8] Rafael C. Gonzalez and Richard E.Woods. Digital Image Processing (Third Edition) Dorling Kindersley Pvt. Ltd., India, 2014.

[9] Cha, et al.,"Update on Brain Tumor Imaging: From Anatomy to Physiology" Americal Journal for Neuroradiology, 2006, Volume 27, pp: 475-487.

[10] Marc C. Mabray, Ramon F. Bajaras and Soonmee Cha, "Modern Brain Tumor Imaging" Brain Research and Treatment Journal, 2015, Volume 3, Issue 1, pp:8- 23.

[11] Timothy L. Jones, Tiernan J. Byrnes, Guang Yang, Franklyn A. Howe, B. Anthony Bell Thomas R. Barrick "Brain Tumor Classification using the Diffusion Tensor Image Segmentation (D-Seg) Technique" Neuro-Oncology, Vol 17, Issue 3, March 2015, pp. 466–476.